Research Article

Science, Engineering and Health Studies
https://li01.tci-thaijo.org/index.php/sehs
ISSN (Online): 2630-0087

Study on demand forecasting techniques for drugs with sporadic demand in a community hospital

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***Received**: 10 May 2021*
***Revised**: 14 June 2021*
***Accepted**: 29 June 2021*
***Published**: 17 June 2022*

***Citation**:*
Thaiudomsap, N., and Sribundit, N. (2022). Study on demand forecasting techniques for drugs with sporadic demand in a community hospital. Science, Engineering and Health Studies, 16, 22050005.

ABSTRACT

This research studied the appropriate forecasting techniques for drugs with sporadic demand, consisting of intermittent and lumpy demands. The actual consumption of 41 drugs in a community hospital from 2014 to 2018 was analyzed to forecast the monthly demand in 2019 using the simple exponential smoothing (SES), Croston, Syntetos-Boylan approximation (SBA), and Teunter, Syntetos, and Babai (TSB) methods and compared the forecasting performance with actual demand. The results revealed that the TSB method performed the best forecast accuracy with the root mean squared error of 12.68, mean absolute deviation of 9.61, and mean absolute scaled error of 1.04. However, it produced a higher bias than others. SES demonstrated the second-best accuracy method, presenting the least bias with the cumulated forecast error of 19.04, the percentage of the number of shortages of 76.91, and the periods in stock of -185.69. Although the SBA method exhibited a lower error than the Croston method, it contributed to a higher bias. As there were no forecasting methods that demonstrated the best forecast accuracy and bias for drugs with sporadic demand, the proper forecasting technique needed to be customized for each drug.

Keywords: forecasting technique; sporadic demand; intermittent demand; lumpy demand; inventory management

1. INTRODUCTION

Drugs play a vital role in the healthcare system: they are crucial in patients' treatment. Therefore, drug inventory management depends heavily on a healthcare provider in supplying sufficient, appropriate, and qualifying drugs to patients in time. Also, efficient drug inventory management leads to the proper administration of drug expenses. However, overstocking drugs risks increased carrying costs and drug expiration, whereas low inventory levels may result in lost sales and influence patients' health (Uthayakumar and Priyan, 2013; Kritchanchai and Meesamut, 2015).

The supply chain of pharmaceutical products is complex and distinctive attributable to the unpredictability of diseases, their treatment, and drug availability; divergent patient, doctor, and health insurance requirements; the market power of patents and brand loyalty; and the impact of industrial policy, health policy, politics, and economics (Candan et al., 2014; Merkuryeva et al., 2019). Furthermore, drug shortage puts pressure on hospitals and affects patients' health. Hence, to provide a desirable quality service, the person responsible for inventory management must have the requisite skills and tools to ensure optimal inventory levels to meet the actual demand (Alves, 2018).

The frequently applied inventory management model includes economic order quantity, which determines the suitable purchasing quantity of products while minimizing expenses. However, numerous assumptions, including constant demand, can limit the implementation of this model (Rachmania and Basri, 2013). Consequently, other models were identified, such as always better control (ABC) analysis; vital, essential, and non-essential (VEN) analysis; and ABC-VEN analysis (Chungsiwapornpong, 2007; Chaiveerathai and Liampreecha, 2015; Pungsak, 2015). However, uncertain demand still resulted in high levels of stock, drug shortages, and nearly expired drugs. Consequently, many hospitals began to adopt demand forecasting techniques in addition to the existing inventory management models, resulting in more efficient inventory repository administration by reducing the occurrence of shortages and lowering stock quantities (Pungsak, 2015; Alves, 2018).

Demand forecasting is one of the tools used to determine the lowest inventory level to satisfy patients' demands. Such forecasting simultaneously minimizes the ordering and holding inventory costs (Thomopoulos, 2015). The demand patterns must be analyzed to execute the forecasting techniques. Then the appropriate methods will be determined based on each consumption pattern (Rachmania and Basri, 2013). The recommended forecasting data in pharmaceuticals is generally acquired from the preceding consumption, that is, the average monthly demand. Besides, additional methods, such as causal, judgmental, and morbidity forecasting, may be used to customize the quantities of drugs to be procured (Dias et al., 2012).

The quantitative forecasting approach can be categorized into time series models, which generate the forecast acquired from the data based on a series of observations over a specified period, and associative models that look for the relationship between each variable and the forecast value. Given that the time series models are the most used techniques in the pharmaceutical industry, it is noteworthy that this research only emphasizes forecasting methods based upon the time series models (Reid and Sanders, 2005; Merkuryeva et al., 2019).

The demand patterns can be classified based on the average inter-demand interval (ADI) and coefficient of variation squared (CV^2) into four categories: smooth, erratic, intermittent, and lumpy (Syntetos et al., 2005). Smooth and erratic demands are aggregated with regularly required products. The traditional methods, such as moving average and simple exponential smoothing (SES), are used to predict demand. However, sporadic demand consisting of intermittent and lumpy demands is more complicated to forecast given its uncertainty and desired techniques, such as Croston, Syntetos-Boylan approximation (SBA), and Teunter, Syntetos, and Babai (TSB) methods (Croston, 1972; Syntetos and Boylan, 2005; Cavalieri et al., 2008; Teunter et al., 2011).

In sporadic demand forecasting, the SES method is one of the traditional models commonly used, as it is straightforward to conceive and apply (Reid and Sanders, 2005). However, Croston remarked that the SES method is not suitable to forecast sporadic demand, given the emphasis on current demand bias. The predicted value is overestimated in the period succeeding the non-zero demand. Therefore, Croston proposed a new method by placing the exponentially weighted moving average value between the non-zero demand size and the time interval of non-zero demand. This model was named the Croston method and is widely used in software packages (Croston, 1972; Babai et al., 2019).

Albeit the Croston method appears to be better than the SES method in forecasting sporadic demand, this model still encounters constraints arising from the expected demand bias and the smoothing constant used for demand intervals (Syntetos and Boylan, 2005; Petropoulos et al., 2016). Additionally, studies revealed that the Croston method performs poorly when real data are applied (Babai et al., 2019; Doszyń, 2019; Yang et al., 2021). The novel SBA method has emerged to solve the problem of the Croston method, and it seems to outperform the Croston method (Eaves and Kingsman, 2004; Syntetos and Boylan, 2005; Petropoulos et al., 2016). However, the SBA method has a negative bias, which could affect the forecasting performance (Teunter and Sani, 2009; Babai et al., 2019).

The Croston and SBA methods seem to update the demand interval, mainly when positive demand takes place. This inertia to revise indicated that these models are unable to deal with obsolescent products. Hence, Teunter, Syntetos, and Babai recommended multiplying the demand size and the probability of a non-zero demand occurrence; this is known as the TSB method. This model revises the probability of demand occurrence in all periods, even though the duration has zero observations. The TSB method tends to be unbiased in a theoretical perspective and has satisfying performances in studies. However, this model appears to under-forecast the demand and is outperformed by the SBA method in some situations (Teunter et al., 2011; Babai et al., 2014; Petropoulos et al., 2016; Babai et al., 2019; Doszyń, 2019; Yang et al., 2021).

Moreover, the proposed forecasting method that emerged to deal with inventory obsolescence is the modified SBA, which updates the forecasting values in every period, including periods with zero demand. Unfortunately, although this method is attractive considering the original study, it results in poor performance when applied to the other datasets and performs worse than the TSB method (Babai et al., 2019; Yang et al., 2021).

Finally, the last proposed method is the modified TSB method, which alters the method to update the demand when there is no actual demand to produce a more accurate forecast. However, when scrutinized on both datasets used in the study, the results make it difficult for a generalized conclusion, and no inventory performance is analyzed for this method (Yang et al., 2021).

Even though various forecasting techniques are recommended for sporadic demand, the studies on medication in healthcare settings are limited. For example, the results from a study in Thailand conducted on two drugs using the Croston and TSB methods are inconclusive in determining which method is superior (Kalaya et al., 2019). The recently published study forecasted the demand for 1,718 medicine products using the SES, Croston, SBA, TSB, modified SBA, and modified TSB methods. The result is also ambiguous (Yang et al., 2021). Furthermore, other studies were conducted in industries other than pharmaceuticals (Teunter et al., 2011; Petropoulos et al., 2016; Babai et al., 2019; Doszyń, 2019).

Consequently, the researchers were interested in examining the forecasting methods for drugs with sporadic demand concentrated on intermittent and lumpy patterns and focused on the four frequently applied forecasting techniques performed in most research: the

SES, Croston, SBA, and TSB methods. Though the SES method was used as the benchmarking model, it was not attractive from a theoretical perspective. When real data was applied, the results sometimes showed a better performance than other methods, such as the Croston method (Babai et al., 2019).

This research used the case study of the Samroiyod Hospital, the middle-sized community hospital in Thailand. The hospital used various tools, such as ABC-VEN analysis to manage its drug inventory. However, drug consumption uncertainty, especially in drugs with sporadic demand, resulted in excessive or inadequate inventory stocks. Therefore, research on forecasting methods for drugs with sporadic demand will aid in selecting the proper techniques to be used with established practices for improved drug inventory management efficiency.

2. MATERIALS AND METHODS

2.1 Notations

The notations used for the entire research article are summarized in Table 1.

Table 1. Notation descriptions

Notation	Description
τ_i	time between two consecutive demand periods
ε_a	average demand of periods with non-zero demand
ε_{ri}	demand in periods
F_t	value of demand forecast in period t
N	number of all periods
N_p	number of periods with non-zero demand
P_t	number of a time interval of non-zero demand in period t
P'_t	estimate of demand interval in period t
p_t	demand occurrence indicator for period t
p'_t	estimate of the probability of a demand occurrence at the end of period t
$Z_{t,i}$	actual demand in period t or i
Z'_t	estimation of mean demand size at the end of period t
α, β	smoothing constant by $0 \leq \alpha, \beta \leq 1$

2.2 Forecasting techniques

The SES method is the traditional model commonly used for intermittent demand forecasting. The model is shown below:

$$F_{t+1} = F_t + \alpha(Z_t - F_t) \quad (1)$$

The Croston method was proposed to correct the bias of the SES by placing the exponentially weighted moving average value between the demand size and time interval. However, it updated the demand interval mainly in periods with non-zero demands. The formula is as below:

$$F_{t+1} = \frac{Z'_t}{P'_t} \quad (2)$$

where $If\ Z_t = 0;\quad Z'_t = Z'_{t-1},\quad P'_t = P'_{t-1}$

$If\ Z_t > 0;\quad Z'_t = Z'_{t-1} + \alpha(Z_t - Z'_{t-1}),$

$P'_t = P'_{t-1} + \alpha(P_t - P'_{t-1})$

The SBA method was introduced to solve the problem of the bias of the Croston method by adding the correction factor $\left(1 - \frac{\alpha}{2}\right)$. The equation is as follows:

$$F_{t+1} = \left(1 - \frac{\alpha}{2}\right)\frac{Z'_t}{P'_t} \quad (3)$$

where $If\ Z_t = 0;\quad Z'_t = Z'_{t-1},\quad P'_t = P'_{t-1}$

$If\ Z_t > 0;\quad Z'_t = Z'_{t-1} + \alpha(Z_t - Z'_{t-1}),$

$P'_t = P'_{t-1} + \alpha(P_t - P'_{t-1})$

The TSB method was proposed by multiplying the demand size and the probability of a non-zero demand occurrence, and it revised the probability of demand occurrence in all periods to deal with obsolescent products. It uses the following formula:

$$F_{t+1} = p'_t Z'_t \quad (4)$$

where $If\ p_t = 0;\quad p'_t = p'_{t-1} + \beta(0 - p'_{t-1}),$

$Z'_t = Z'_{t-1}$

$If\ p_t > 0;\quad p'_t = p'_{t-1} + \beta(1 - p'_{t-1}),$

$Z'_t = Z'_{t-1} + \alpha(Z_t - Z'_{t-1})$

2.3 Experiments

2.3.1 Forecasting procedure

This research was descriptive research that used retrospective data to analyze and forecast sporadic demand, consisting of intermittent and lumpy demands. The dataset originated from the Samroiyod Hospital. The flowchart of the research procedure established in this research is illustrated in Figure 1.

The monthly demand for drugs over six years from 2014 to 2019 (72 months) was gathered. The accumulated data was segregated into initialization (the first 60 months) and performance (the last 12 months) blocks.

The demand patterns for demand forecasting could be designated into four groups that relied on the ADI and CV^2, by using the data in the initialization section, which could be calculated by:

$$ADI = \frac{\sum_{i=1}^{N} \tau_i}{N_p}$$

$$CV^2 = \left(\frac{\sqrt{\frac{\sum_{i=1}^{N}(\varepsilon_{ri} - \varepsilon_a)^2}{N_p}}}{\varepsilon_a}\right)^2, \text{ where } \varepsilon_a = \frac{\sum_{i=1}^{N} \varepsilon_{ri}}{N_p}.$$

The four demand patterns were differently elucidated by (Syntetos et al., 2005): smooth demand (ADI $\leq$ 1.32 and CV^2 $\leq$ 0.49), erratic demand (ADI $\leq$ 1.32 and CV^2 > 0.49), intermittent demand (ADI > 1.32 and CV^2 $\leq$ 0.49), lumpy demand (ADI > 1.32 and CV^2 > 0.49).

The intermittent and lumpy demands were exclusively sorted to compute a suitable smoothing constant value for each product. Descriptive statistics were used to enumerate the distribution of intermittent and lumpy demand data.

The wide range of alpha smoothing constant values used in the SES, Croston, SBA, and TSB methods was explored within 0.05-0.30, with a step increase of 0.05. The beta smoothing range for TSB was the same as alpha, with the additional range of 0.01-0.05 and the step equal to 0.01 (Sayed et al., 2010; Babai et al., 2019).

The estimated initial values for each forecasting technique were acquired from the initialization block. The starting estimates were composed of average demand in SES, average demand size and demand interval in the Croston and SBA methods, and average demand size and demand occurrence probability in the TSB method.

The suitable smoothing constants and the estimated initial values for each drug in each forecasting technique from the initialization block were then used to generate the forecast from the SES, Croston, SBA, and TSB methods for 12 consecutive months.

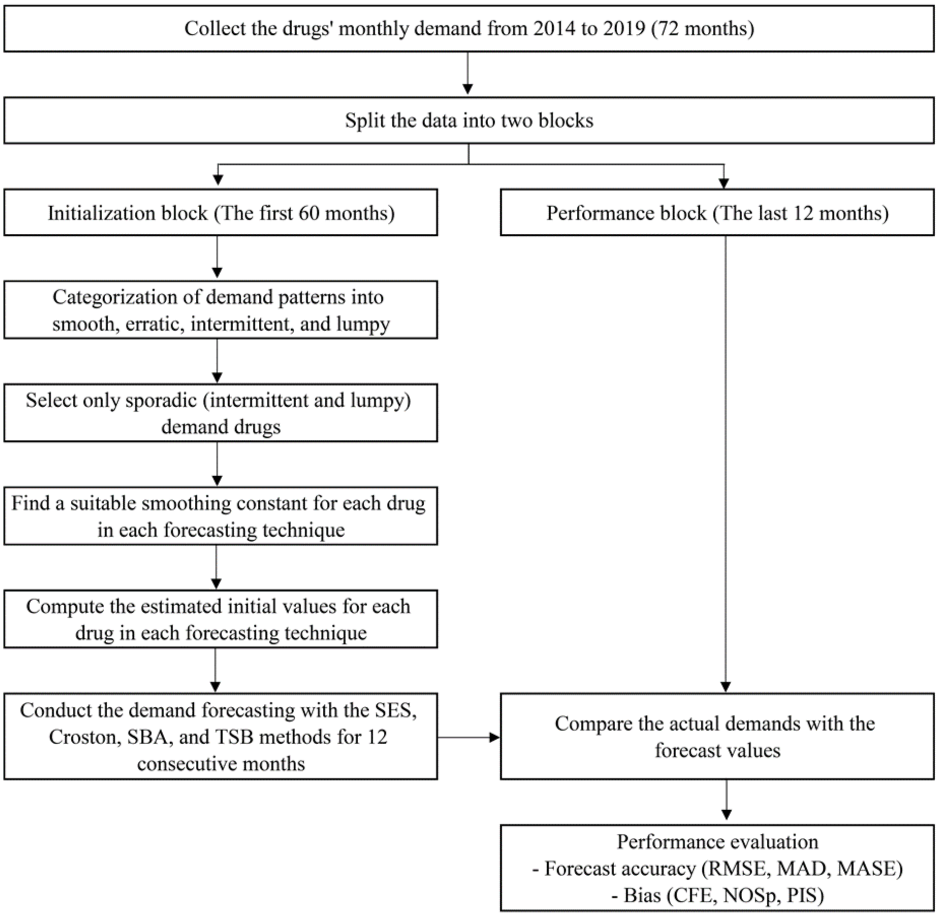

Figure 1. The flowchart of the research procedure

2.3.2 Forecasting performance measurement

The forecasting performances for all investigated methods were assessed for forecast accuracy and bias (systematic error) by comparing actual demands in the performance block with forecast values generated from the initialization block. As there was no single performance measurement that worked as the best measure, we used the multiple accuracy measures, containing root mean squared error (RMSE), mean absolute deviation (MAD), and mean absolute scaled error (MASE). These measures are commonly used in studies. They are more appropriate than other measures, such as mean absolute percentage error, which yield the infinite value when applied to sporadic demand dataset (Hyndman and Koehler, 2006; Babai et al., 2019; Doszyń, 2019; Kalaya et al., 2019; Yang et al., 2021). The method demonstrating the best forecast accuracy will generate the lowest error. The formulas are presented in Table 2.

Table 2. Formulas for forecasting accuracy measurement

Forecasting accuracy	Formula
Mean absolute deviation (MAD)	$\frac{\sum_{t=1}^{N} \lvert Z_t - F_t \rvert}{N}$
Root mean squared error (RMSE)	$\sqrt{\frac{\sum_{t=1}^{N} (Z_t - F_t)^2}{N}}$
Mean absolute scaled error (MASE)	$\frac{\frac{1}{N}\sum_{t=1}^{N} \lvert Z_t - F_t \rvert}{\frac{1}{n-1}\sum_{i=2}^{n} \lvert Z_i - Z_{i-1} \rvert}$

The mean error (ME), usually used as bias measurement, had the disadvantage of the positive and negative errors in different periods canceling each other (Doszyń, 2018; Yang et al., 2021). Therefore, the bias measures in this research considered the cumulated forecast error (CFE), the percentage of the number of shortages (NOSp), and periods in stock (PIS), which Wallström and Segerstedt suggested to overcome the ME pitfall. The details on bias measurement were described in Wallström and Segerstedt (2010). Accordingly, the method that revealed the best bias would present the value closest to zero. The formulas are expressed in Table 3.

Table 3. Formulas for forecasting bias measurement

Bias	Formula
Cumulated forecast error (CFE)	$CFE_t = \sum_{i=1}^{t} (Z_t - F_t),\quad t = 1,2,\dots,T$
Percentage of the number of shortages (NOSp)	$If\ Z_t \neq 0\ and\ CFE_t > 0\ then\ NOS \leftarrow NOS + 1,\quad t = 1,2,\dots,T$ $NOSp = \frac{NOS}{N} x100$
Periods in stock (PIS)	$PIS_t = PIS_{t-1} + \sum_{i=1}^{t} (F_t - Z_t)$ $= \sum_{i=1}^{t} (F_t\text{-}Z_t)\,(t + 1 - i)$ $PIS_t = PIS_{t-1} - CFE_t$ $= -\sum_{i=1}^{t} CFE_i$ $PIS_T = -\sum_{t=1}^{T} CFE_t$

2.4 Assumptions

This research had been subject to the following assumptions. First, the drug demand only depended on time to eliminate the influence of the other factors that might affect the demand, such as medication use policies. Second, there was one brand name used for each drug in the hospital. Third, the demand forecasting was based on the smallest unit for each drug, such as a tablet, bottle, ampoule, and vial. Last, medications with no demand during the forecasting periods would not be incorporated into the analysis as some forecasting performance indicators, for example, MASE and NOSp, would generate infinite values.

3. RESULTS AND DISCUSSION

The analyzed monthly consumption data in the initialization block could allocate the drugs into four demand pattern categories based on the ADI and CV^2 with the cut points of 1.32 and 0.49, respectively. Out of 348 products, 20 items (5.75%) were classified as intermittent demand, and 23 items (6.61%) were categorized as lumpy demand. The dispersion of the ADI and CV^2 for each demand pattern can be found in Table 4.

Table 4. The dispersion of the ADI and CV^2 for drugs with intermittent and lumpy demand

Dispersion	Intermittent demand (n = 20)		Lumpy demand (n = 23)	
	ADI	CV^2	ADI	CV^2
Mean	3.87	0.29	2.59	1.36
Standard deviation	2.60	0.11	1.41	2.30
Maximum	10.00	0.48	6.67	12.02
Minimum	1.54	0.11	1.36	0.50

From Table 4, drugs with intermittent and lumpy demands had an average ADI of 3.87 ± 2.60 and 2.59 ± 1.41 months, respectively, which were greater than 1.32 months. Whereas the average CV^2 of intermittent demand was 0.29 ± 0.11, which was below 0.49, the lumpy demands' average CV^2 was 1.36 ± 2.30, exceeding 0.49.

Since there was no green pit viper antivenom and tiotropium consumption in the performance block, these two items were excluded from demand forecasting.

The forecasting techniques used in this research involved the SES, Croston, SBA, and TSB methods. Each model's smoothing constant value (α = 0.05-0.30, β = 0.01-0.30) was selected based on the minimum RMSE, which offered a lower error than the other accuracy measures. Then, the forecast accuracy and bias for each forecasting method were computed using averages of the intermittent and lumpy demands as presented in Table 5 and Table 6 sequentially.

The intermittent demand forecasting of the 19 drugs in Table 5 indicated that the TSB method outperformed others in forecasting errors for all accuracy measures. The accuracy estimates of the SES method were superior to the Croston and SBA methods. Nevertheless, the SES and Croston methods exhibited lower biases when biases were examined than the SBA and TSB methods. The graph revealed a comparison between actual consumption and forecasting values for the streptomycin injection in the intermittent demand are shown in Figure 2.

The outcome in Table 6 illustrated the forecast performances of the 22 drugs with lumpy demand. The TSB method also outperformed other techniques based on RMSE and MAD, whereas the SES method performed best when the MASE was determined. Besides, the Croston and SBA methods remained at a higher degree of error than others. When deliberated on the whole bias, the SES method was found to have the least bias, whereas the SBA method had the most significant bias. The graph in Figure 3 showed a collation between actual consumption and forecasting values for the benzyl benzoate suspension, which is a lumpy demand drug.

Table 5. The average forecast accuracy and bias for drugs with intermittent demand (n = 19)

Forecasting methods	α	β	RMSE	MAD	MASE	CFE	NOSp	PIS
SES	0.14		5.06	3.86	1.34	2.38	85.77	-44.61
Croston	0.19		5.21	4.00	1.66	3.69	77.69	-42.73
SBA	0.23		5.18	3.88	1.54	10.79	85.44	-88.26
TSB	0.22	0.15	4.99	3.68	1.27	8.37	88.65	-76.77

Table 6. The average forecast accuracy and bias for drugs with lumpy demand (n = 22)

Forecasting methods	α	β	RMSE	MAD	MASE	CFE	NOSp	PIS
SES	0.15		18.69	14.75	0.83	33.42	69.26	-307.54
Croston	0.16		19.14	14.90	0.85	40.19	70.16	-323.17
SBA	0.18		19.15	14.79	0.85	58.92	71.20	-434.98
TSB	0.22	0.17	18.58	14.74	0.84	39.92	70.51	-377.25

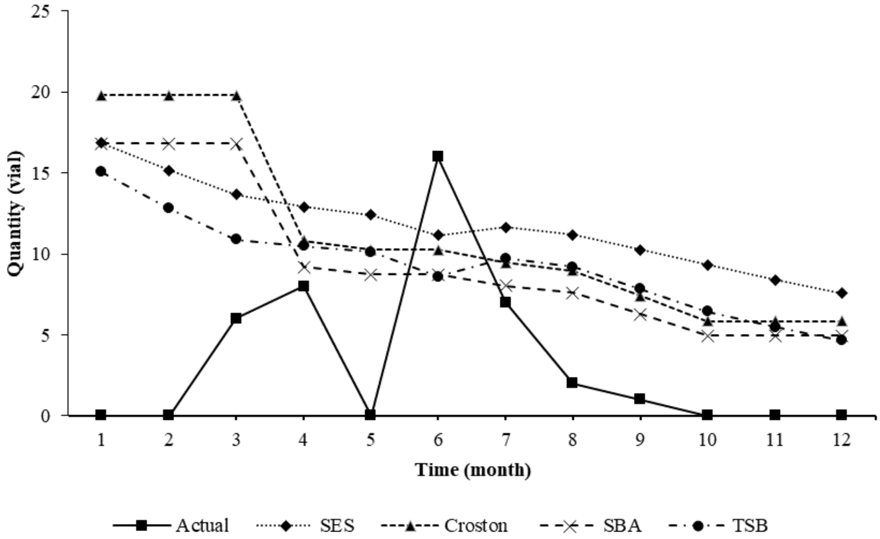

Figure 2. The comparison between actual consumption and forecasting values from the SES, Croston, SBA, and TSB methods for the streptomycin injection

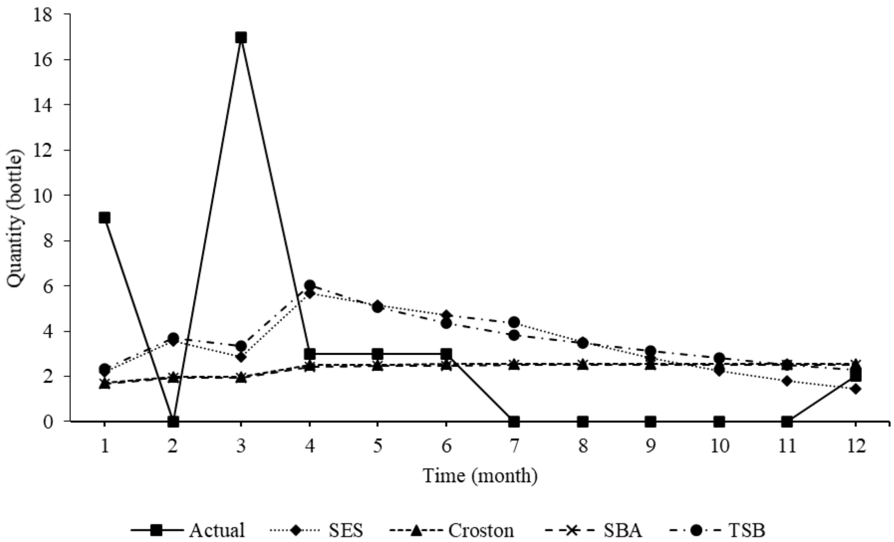

Figure 3. The comparison between actual consumption and forecasting values from the SES, Croston, SBA, and TSB methods for the benzyl benzoate suspension

In the benzyl benzoate suspension demand forecasting shown in Figure 3, the third month's actual demand dramatically increased. The methods used in this research might not provide sufficient accurate forecasts. Although the forecasting error might be low due to the average error in the 12 periods, the third month's error was high. There was a drug shortage from the low forecast compared to the actual demand, which inflated the bias. Moreover, the seventh to the eleventh-month forecast was higher than the actual demand, resulting in overstock and increasing the bias. Therefore, the forecasting error might be low, but the bias was high, indicating an inappropriate use of the methods applied in this research.

To examine the overall forecasting performances for sporadic demand drugs, we incorporated the data from both intermittent and lumpy demands and calculated the average forecast accuracy and bias for each forecasting method as presented in Table 7.

Table 7. The average forecast accuracy and bias for drugs with sporadic demand (n = 41)

Forecasting methods	α	β	RMSE	MAD	MASE	CFE	NOSp	PIS
SES	0.15		12.37	9.70	1.07	19.04	76.91	-185.69
Croston	0.17		12.69	9.85	1.22	23.27	73.65	-193.21
SBA	0.20		12.68	9.73	1.17	36.61	77.80	-274.31
TSB	0.22	0.16	12.28	9.61	1.04	25.30	78.92	-238.00

As seen in Table 7, when the forecast accuracy for 41 drugs with sporadic demand consisting of RMSE, MAD and MASE was evaluated, the TSB method outperformed other methods for all efficiency measures. The second-best performing method for sporadic demand forecasting was SES, which was unexpected from a theoretical perspective, and was caused by the demand update in every period. Furthermore, the Croston method exhibited the highest error, corresponding to accuracy measures in the other research (Babai et al., 2019; Doszyń, 2019; Yang et al., 2021). The poor performance could be explained by the inability to respond to the changes in demand in the Croston and SBA methods, which updated the demand interval only when positive demand occurred, resulting in a lower forecast accuracy than the TSB and SES methods. When the forecasting bias was examined, the results showed that the SES method had the least bias when determining CFE, NOSp, and PIS. Although the SBA method resulted in fewer errors than the Croston method, it revealed a higher degree of bias and had the greatest bias of all methods. This finding arose from the correction factor $\left(1-\frac{\alpha}{2}\right)$ being applied to correct the bias in the Croston method. However, some negative bias remained, which affected the forecasting performance, as mentioned earlier. Finally, it was not surprising that TSB yielded the best forecast accuracy but demonstrated the greatest bias. The TSB method minimized stock to reduce obsolescence, resulting in an under-forecast of the demand.

In summary, the results revealed that the TSB method provided a minimum forecast error. However, it exhibited a greater extent of bias than others. The SES method performed the next-best efficient procedure as it was the least biased. The SBA method presented a smaller error than the Croston method, but it contributed to more bias. This research aimed to obtain the proper forecasting technique for drugs with sporadic demand that manifests with the highest accuracy and the smallest bias. The results exhibited an inconclusive solution for generalization.

The results corresponded with previous research (Yang et al., 2021) that forecast intermittent demand drugs. Compared with the methods applied in this study, the results were inconclusive for which method performs best. The SES method performed best when the mean squared error (MSE) was considered, whereas the TSB method manifested the highest forecast error. However, the result was different from the MASE that the TSB method performed the smallest error. When bias measured by the ME was examined, the results revealed that the TSB method had the highest bias.

The results also concord with other research (Kalaya et al., 2019) that forecasted furosemide injection and adrenaline injection demand using the TSB and Croston methods. The research inconclusively found that the TSB method had a lower MSE than the Croston method for adrenaline injection but was contradicted for the furosemide injection. This result might be due to more frequent demand and higher consumption than the average demand, which generated a lower forecast accuracy. Nevertheless, the number of shortages for Croston was lower than for the TSB method, which was consistent with this research. The explanation is that the Croston method updates the forecasting value only in periods with positive demand, responding slower to the change in demand than the TSB method, which updates the forecasting demand in all periods to reduce inventory obsolescence.

Other research on sporadic demand forecasting was frequently explored in spare parts businesses, such as Hemeimat et al. (2016) and Babai et al. (2019). The findings also demonstrated that although the TSB method seemed to have the best forecast accuracy, it had a higher bias than others. Consequently, the results were similarly inconclusive in forecasting which methods had the highest accuracy and the least bias. However, it is worth noting that the research was conducted for a product in a different industry to this study. Furthermore, the types of demand were disparate between spare parts, which belonged to dependent demand, and drugs, which belonged to independent demand.

The forecasting performance can be evaluated through forecast accuracy and bias. The forecast accuracy determines the magnitude of error irrespective of the direction (Wild, 2002). The error generated from this measure emphasizes the comparison between the forecast with actual demand at each time point. However, the bias demonstrates either an over-forecast or under-forecast tendency when collating the forecast with actual consumption (Wallström and Segerstedt, 2010). Thus, bias tends to indicate the trend of overall inventory performance. Hence, the appropriate forecasting method based on a single performance measure may result in a misleading finding.

If we focus on accuracy measures, the low forecasting error may not show that the error between forecast and actual values will be small at all time points. The average error when all time points are considered, and if any point of forecast showed a high forecasting error, can be reduced through distribution over the period that exhibited a low error.

While emphasizing the bias, we recognize the error's direction. The entire forecasted inventory is higher or lower than the actual demand. However, this measure also has the constraint of a forecasting method with a low bias presenting as a high forecast error. For instance, the method that over-forecasts the demand will result in a high forecast error. However, when the NOSp is considered, this method's bias is low as the over-forecast stock will not be counted as a shortage.

Drug shortages not only influence the ability to service patients, but they can also significantly impact patients' health. Therefore, the forecasting performance assessment for drugs should be concentrated on bias rather than forecast accuracy to prevent drug shortages, even if the trade-off is a small inventory overstock.

Furthermore, some drug categories may not be suitable for a particular forecasting technique. For example, the vital drugs classified by VEN analysis are a group of medicines that should be available at all times. Thus, drug shortage of critical medications is a significant problem. In this situation, even though the TSB method has the best forecasting accuracy, it produced more drug shortages than the others and should not be used for forecasting vital medicines.

This study demonstrated sporadic demand forecasting for drugs in a community hospital. However, there are some considerations when applying demand forecasting in other hospitals and healthcare settings. As there was no particular forecasting method suitable for all medicines within an identical demand pattern, the demand patterns should be analyzed to determine any explanatory cause of unusual consumption to select the appropriate forecasting technique. Suppose there is an explanation to describe the origin of outliers' demand, then the forecasting methods that suit these demand patterns will be adopted. For example, when forecasting the seasonal characteristics of a sporadic demand drug, it will be preferable to forecast using Winters' seasonality exponential smoothing rather than the methods applied in this research. However, if there is no reason to clarify the nature of outliers and no suitable techniques for the dataset proposed, the outliers' demand may be excluded; the forecasting techniques used in this research may provide more accurate forecasts. However, demand may frequently fluctuate, so it is essential to revise the demand pattern annually.

As highlighted in this research, the methods are related to time series models. Thus, a limitation should be considered before implementing these procedures: the time series model specifies the assumption that demand depends on time. However, the existing demand may have additional factors that influence the uncertainty of demand apart from time, such as the variability in disease treatment, health insurance regulations, market power of patents and brand loyalty, and the impact of policies (Candan et al., 2014; Merkuryeva et al., 2019).

4. CONCLUSION

There was no forecasting method suitable for all drugs with sporadic demand: Consequently, the proper forecasting technique needed to be customized for each drug based on its demand characteristics. The demand pattern should be considered first to find any explanatory cause of unusual consumption, and the forecasting methods that suit these demand patterns should be applied. However, if there is no reason to clarify the nature of outliers, no suitable techniques for the dataset are proposed. Consequently, the outliers' demand could be excluded, and the forecasting techniques exercised in this research could make the forecasts more precise.

Given the scarcity of data in the pharmaceutical setting, it is suggested that future research explores the sporadic demand drugs to gain more insight through other forecasting models such as nonparametric forecasting and machine learning. Another interesting area for future work is to conduct the inventory performances with other indicators such as days of supply, average inventory level, and inventory turnover to make the evaluation more thorough.

REFERENCES

Alves, C. M. F. (2018). *Demand forecasting in a multi-specialty hospital setting: a comparative study of machine learning and classical statistical methods*. Master's thesis. University of Porto, Portugal.

Babai, M. Z., Dallery, Y., Boubaker, S., and Kalai, R. (2019). A new method to forecast intermittent demand in the presence of inventory obsolescence. *International Journal of Production Economics*, 209, 30-41.

Babai, M. Z., Syntetos, A., and Teunter, R. (2014). Intermittent demand forecasting: an empirical study on accuracy and the risk of obsolescence. *International Journal of Production Economics,* 157, 212-219.

Candan, G., Taşkin, M. F., and Yazgan, H. R. (2014). Demand forecasting in pharmaceutical industry using artificial intelligence: neuro-fuzzy approach. *Journal of Military and Information Science*, 2(2), 41-49.

Cavalieri, S., Garetti, M., Macchi, M., and Pinto, R. (2008). A decision-making framework for managing maintenance spare parts. *Production Planning & Control*, 19(4), 379-396.

Chaiveerathai, S., and Liampreecha, W. (2015). Optimization and cost reduction of pharmaceutical inventory management: a case study of a government hospital in Phitsanulok. *Journal of Community Development Research (Humanities and Social Sciences)*, 8(3), 139-153. [in Thai]

Chungsiwapornpong, W. (2007). *Survey of drug inventory control process and performance among hospital pharmacy departments in Thailand.* Master's thesis. Mahidol University, Thailand.

Croston, J. D. (1972). Forecasting and stock control for intermittent demands. *Operational Research Quarterly*, 23(3), 289-303.

Dias, V., Quick, J. D., and Rankin, J. R. (2012). Inventory management. In *MDS-3: Managing access to medicines and health technologies* (Embrey, M., ed.), pp. 1-24. Arlington, Virginia: Management Science for Health.

Doszyń, M. (2018). New forecasting technique for intermittent demand, based on stochastic simulation. An alternative to Croston's method. *Acta Universitatis Lodziensis, Folia Oeconomica*, 5(338), 41-55.

Doszyń, M. (2019). Intermittent demand forecasting in the enterprise: empirical verification. *Journal of Forecasting,* 38(5), 459-469.

Eaves, A. H. C., and Kingsman, B. G. (2004). Forecasting for ordering and stock holding of spare parts. *Journal of the Operational Research Society*, 55(4), 431-437.

Hemeimat, R., Al-Qatawneh, L., Arafeh, M., and Masoud, S. (2016). Forecasting spare parts demand using statistical analysis. *American Journal of Operations Research*, 6(2), 113-120.

Hyndman, R. J., and Koehler A. B. (2006). Another look at measures of forecast accuracy. *International Journal of Forecasting*, 22(4), 679-688.

Kalaya, P., Termsuksawad, P., and Wasusri, T. (2019). Lumpy demand forecasting for slow-moving medicines: a case study of community hospital Thailand. *Isan Journal of Pharmaceutical Science*, 15(1), 82-92. [in Thai]

Kritchanchai, D., and Meesamut, W. (2015). Developing inventory management in hospital. *International Journal of Supply Chain Management*, 4(2), 11-19.

Merkuryeva, G., Valberga, A., and Smirnov, A. (2019). Demand forecasting in pharmaceutical supply chains: a case study. *Procedia Computer Science*, 149(C), 3-10.

Petropoulos, F., Kourentzes, N., and Nikolopoulos, K. (2016). Another look at estimators for intermittent demand. *International Journal of Production Economics*, 181(A), 154-161.

Pungsak, A. (2015). *Precision and effectiveness of demand forecasting for drug inventory management.* Master's thesis. Silpakorn University, Thailand.

Rachmania, I. N., and Basri, M. H. (2013). Pharmaceutical inventory management issues in hospital supply chains. *Management*, 3(1), 1-5.

Reid, R. D., and Sanders, N. R. (2005). *Operations Management: an Integrated Approach*, 2nd, New Jersey: John Wiley & Sons, Inc., pp. 280-330.

Sayed, H. E., Gabbar, H. A., and Miyazaki, S. (2010). Design of demand forecasting expert system for dynamic supply chains. In *Expert Systems* (Vizureanu, P., ed.), pp. 137-160. Vukovar, Croatia: IntechOpen Ltd.

Syntetos, A. A., and Boylan, J. E. (2005). The accuracy of intermittent demand estimates. *International Journal of Forecasting*, 21(2), 303-314.

Syntetos, A. A., Boylan, J. E., and Croston, J. D. (2005). On the categorization of demand patterns. *Journal of the Operational Research Society*, 56(5), 495-503.

Teunter, R., and Sani, B. (2009). On the bias of Croston's forecasting method. *European Journal of Operational Research*, 194(1), 177-183.

Teunter, R. H., Syntetos, A. A., and Babai, M. Z. (2011). Intermittent demand: linking forecasting to inventory obsolescence. *European Journal of Operational Research*, 214(3), 606-615.

Thomopoulos, N. T. (2015). *Demand Forecasting for Inventory Control*. Switzerland: Springer Cham, pp. 1-10.

Uthayakumar, R., and Priyan, S. (2013). Pharmaceutical supply chain and inventory management strategies: optimization for a pharmaceutical company and a hospital. *Operations Research for Health Care*, 2(3), 52-64.

Wallström, P., and Segerstedt, A. (2010). Evaluation of forecasting error measurements and techniques for intermittent demand. *International Journal of Production Economics*, 128(2), 625-636.

Wild, T. (2002). *Best Practice in Inventory Management*, 2nd, Oxford: Butterworth-Heinemann, pp. 33-186.

Yang, Y., Ding, C., Lee, S., Yu, L., and Ma, F. (2021). A modified Teunter-Syntetos-Babai method for intermittent demand forecasting. *Journal of Management Science and Engineering*, 6(1), 53-63.